

## Week-12

Aim: to implement a deep convolutional Generative Adversarial network (dCGAN) of generating complex RGB colour image that resemble real-world images

### objective:

- 1, to understand the working of Generative Adversarial network (GAN's)
- 2, to use convolutional layer for image generation and discrimination
- 3, to teach the Generator to produce realistic image and the discriminator to distinguish real from fake
- 4, to evaluate the quality of Generated images visually after training.

### pseudo code:

Begin

load dataset of real colour images  
→ Resize and normalize image to  $(1,1)$

Define Generator Network (G):

input: random noise vector (z)

layer: Series of conv Transpose 2D + BatchNorm + ReLU

output: RGB image.

Define Discriminator Network (D):

input: RGB Image

layer: Series of conv 2D + Batch Norm + leaky ReLU

output: single probability

Set loss function = Binary cross entropy

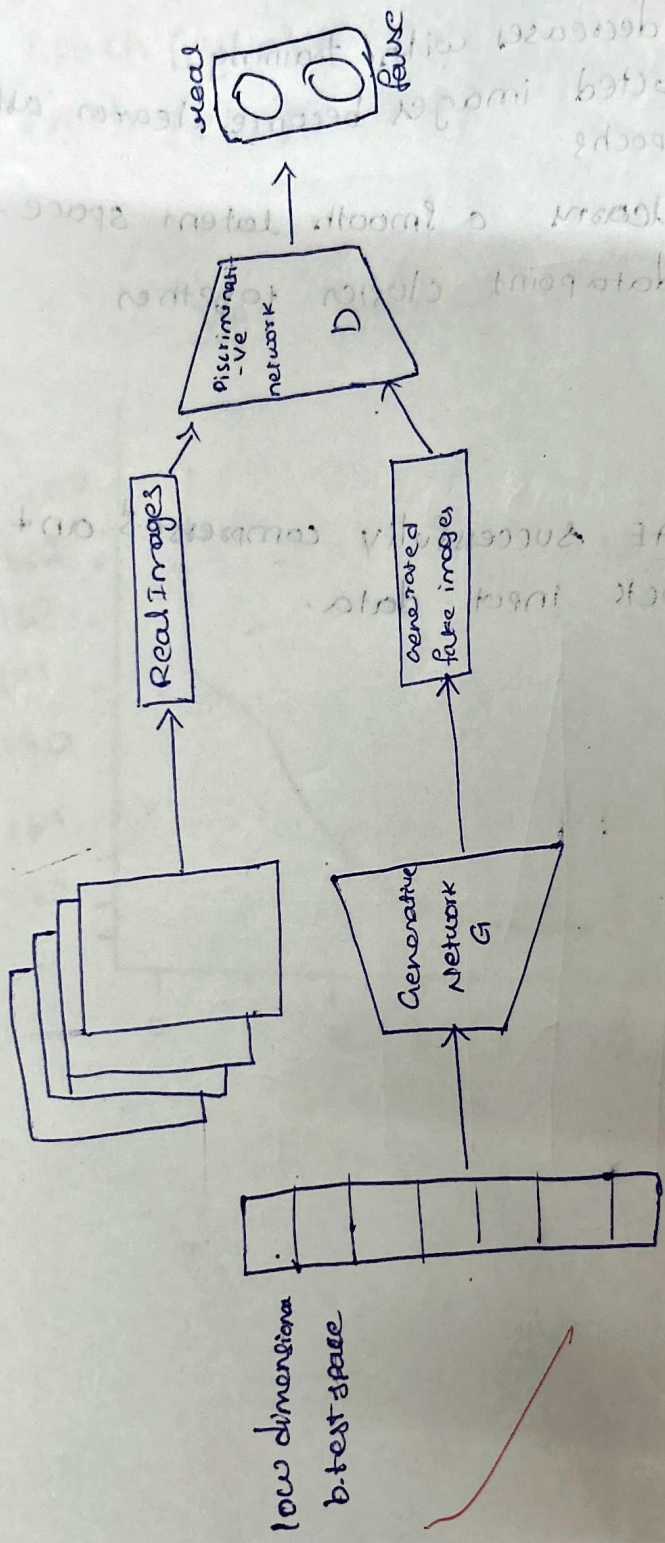
set optimizer = Adam ( $\alpha = 0.0002$ ,  $\beta_1 = 0.5$ )

for each epoch

train discriminator



# GAN Architecture for image



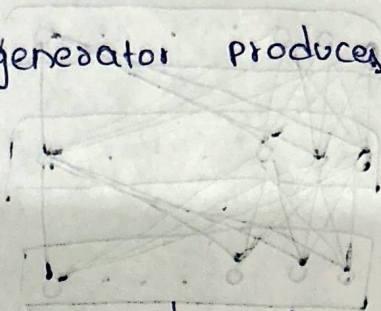


train Generator

Repeat until generator produces realistic colour images ~~END~~

END

### Algorithm:



- 1, load a colour image dataset
- 2, Normalize pixel value to  $[-1, 1]$
- 3, Define generator using conv 2D transpose layer
- 4, Define discriminator using conv 2D layers
- 5, combine both to form DCGAN
- 6, Train using adversarial loss - generator tries to fool discriminator
- 7, periodically generate and display fake images

### observation:

- the generator gradually learned to produce realistic colour images
- the discriminator improved in distinguishing real and fake images
- Generated images were visually similar to the training dataset after sufficient epochs
- training demonstrated the adversarial learning process of GAN effectively

### Result:-

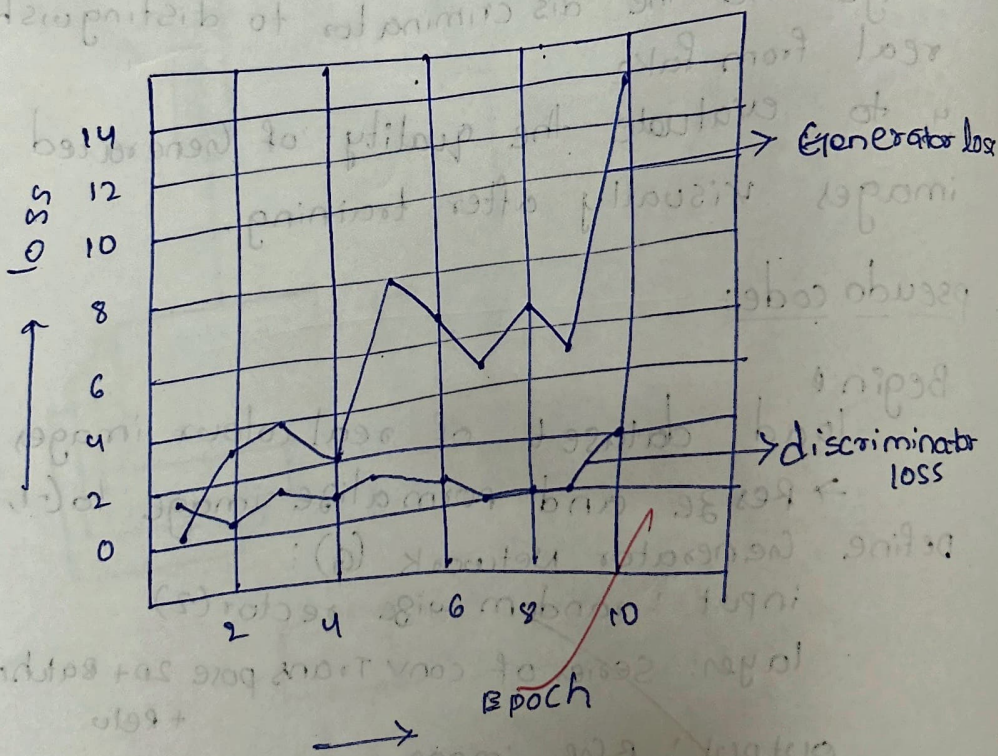
~~The DCGAN~~ successfully generated realistic looking colour images, proving the effectiveness of adversarial learning.



Output :

Epoch [1/10] D Loss : 1.0992 ; G Loss : 0.5678  
 Epoch [2/10] D Loss : 0.5060 ; G Loss : 2.7113  
 Epoch [3/10] D Loss : 1.2431 ; G Loss : 3.9827  
 Epoch [4/10] D Loss : 0.4229 ; G Loss : 2.2684  
 Epoch [5/10] D Loss : 1.1456 ; G Loss : 8.1007  
 Epoch [6/10] D Loss : 1.0081 ; G Loss : 6.7625  
 Epoch [7/10] D Loss : 0.0252 ; G Loss : 4.5718  
 Epoch [8/10] D Loss : 0.0043 ; G Loss : 6.3371  
 Epoch [9/10] D Loss : 0.1890 ; G Loss : 4.7357  
 Epoch [10/10] D Loss : 2.3294 ; G Loss : 14.0363

Epoch vs loss (GAN)



```

# Lab 12 (Fast Version): DCGAN to Generate Color Images (CIFAR-10)
import tensorflow as tf
from tensorflow.keras import layers
import matplotlib.pyplot as plt
import numpy as np
import time

(x_train, _), (_, _) = tf.keras.datasets.cifar10.load_data()
x_train = (x_train.astype("float32") - 127.5) / 127.5 # normalize to [-1,1]
x_train = x_train[:5000] # only 5k images for faster training

BUFFER_SIZE = 5000
BATCH_SIZE = 32
train_dataset = tf.data.Dataset.from_tensor_slices(x_train).shuffle(BUFFER_SIZE).batch(BATCH_SIZE)

def build_generator():
    model = tf.keras.Sequential([
        layers.Input(shape=(100,)),
        layers.Dense(8*8*128, use_bias=False),
        layers.BatchNormalization(),
        layers.LeakyReLU(),
        layers.Reshape((8, 8, 128)),
        layers.Conv2DTranspose(64, (5,5), strides=(2,2), padding="same", use_bias=False),
        layers.BatchNormalization(),
        layers.LeakyReLU(),
        layers.Conv2DTranspose(3, (5,5), strides=(2,2), padding="same", use_bias=False, activation="tanh"),
    ])
    return model

def build_discriminator():
    model = tf.keras.Sequential([
        layers.Input(shape=(32, 32, 3)),
        layers.Conv2D(64, (5,5), strides=(2,2), padding="same"),
        layers.LeakyReLU(),
        layers.Dropout(0.3),
        layers.Conv2D(128, (5,5), strides=(2,2), padding="same"),
        layers.LeakyReLU(),
        layers.Dropout(0.3),
        layers.Flatten(),
        layers.Dense(1)
    ])
    return model

generator = build_generator()
discriminator = build_discriminator()

cross_entropy = tf.keras.losses.BinaryCrossentropy(from_logits=True)
gen_optimizer = tf.keras.optimizers.Adam(1e-4)
disc_optimizer = tf.keras.optimizers.Adam(1e-4)

@tf.function
def train_step(images):
    noise = tf.random.normal([BATCH_SIZE, 100])
    with tf.GradientTape() as gen_tape, tf.GradientTape() as disc_tape:
        generated_images = generator(noise, training=True)
        real_output = discriminator(images, training=True)
        fake_output = discriminator(generated_images, training=True)
        gen_loss = cross_entropy(tf.ones_like(fake_output), fake_output)
        disc_loss = (
            cross_entropy(tf.ones_like(real_output), real_output)
            + cross_entropy(tf.zeros_like(fake_output), fake_output)

```



```

        data = data[0]
        z_mean, z_log_var, z = self.encoder(data)
        reconstruction = self.decoder(z)
        reconstruction_loss = tf.reduce_mean(
            tf.keras.losses.binary_crossentropy(data, reconstruction) * 784
        )
        kl_loss = -0.5 * tf.reduce_mean(
            1 + z_log_var - tf.square(z_mean) - tf.exp(z_log_var)
        )
        total_loss = reconstruction_loss + kl_loss
        return {"loss": total_loss}

```

#### # 5 Compile and Train

```

vae = VAE(encoder, decoder)
vae.compile(optimizer=tf.keras.optimizers.Adam())
history = vae.fit(
    x_train,
    x_train,
    epochs=10,
    batch_size=256,
    validation_data=(x_test, x_test),
)

```

#### # 6 Plot Training vs Validation Loss

```

plt.plot(history.history["loss"], label="Training Loss")
plt.plot(history.history["val_loss"], label="Validation Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.title("VAE Training vs Validation Loss")
plt.show()

```

#### # 7 Reconstruct Test Images

```

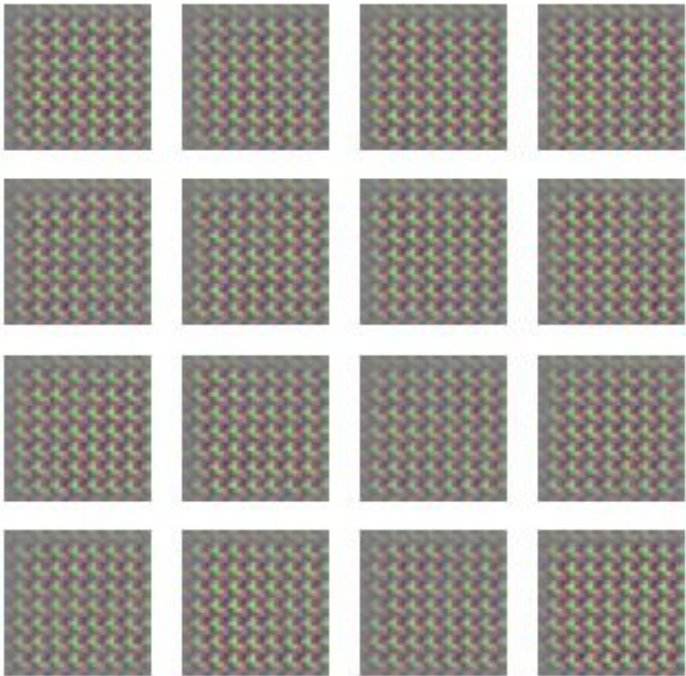
decoded_imgs = vae.decoder(vae.encoder(x_test)[2]).numpy()

n = 10
plt.figure(figsize=(20, 4))
for i in range(n):
    # Original
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test[i].reshape(28, 28), cmap="gray")
    plt.axis("off")
    # Reconstructed
    ax = plt.subplot(2, n, i + 1 + n)
    plt.imshow(decoded_imgs[i].reshape(28, 28), cmap="gray")
    plt.axis("off")
plt.suptitle("Top: Original Images | Bottom: VAE Reconstructions")
plt.show()

```

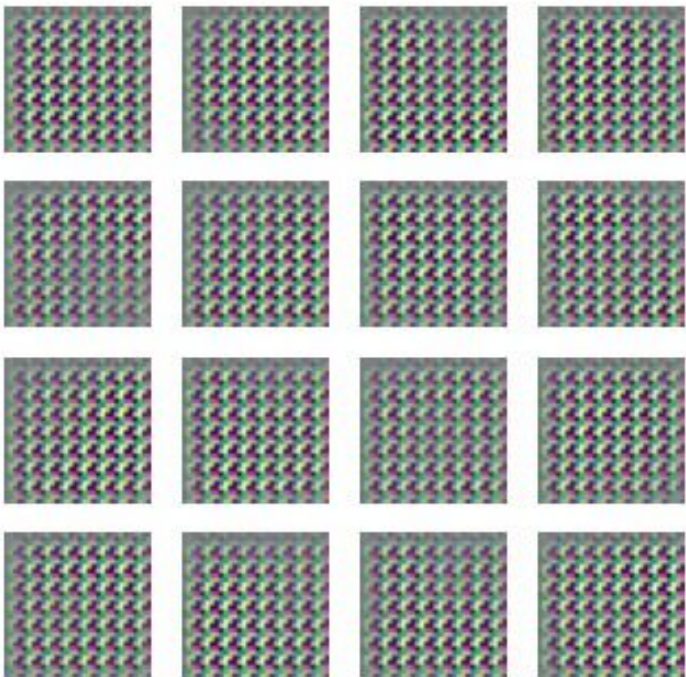
Epoch 1/2 | Gen Loss: 2.6906 | Disc Loss: 0.2989 | Time: 36.21s

Generated Images - Epoch 1



Epoch 2/2 | Gen Loss: 4.3347 | Disc Loss: 0.0647 | Time: 29.22s

Generated Images - Epoch 2



DCGAN Training Loss

